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Shape Optimization of Gravity Dams Using a Nature-Inspired Approach

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ABSTRACT

In water infrastructures design problems, small changes in their geometries lead to a major variation in the construction time and costs. Dams are such important water infrastructures, which have different types regarding their materials and their behavior to endure loads. In the current paper, invasive weed optimization (IWO) algorithm is employed to find the best shape of a concrete gravity dam (Tilari Dam, India). Stress and stability were considered as design constraints, based on the following models: Model I (M1): upstream dam face is inclined and Model II (M2): upstream dam face is vertical. Optimization using IWO for M1 showed 20% reduction in cross-sectional area as compared to prototype. Although results obtained using IWO showed no changes in comparison with the algorithms in the literature (i.e., differential evolution, charged system search, colliding bodies optimization, and enhanced colliding bodies optimization), it converged faster. But results for M2 revealed 26% reduction in cross-sectional area.

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1. Introduction

Dams are essential infrastructures, which are built all over the world for meeting various water demands, including flood control, water supply (urban, domestic, industrial etc.), electricity generation, recreational activities, navigation, groundwater recharge etc.

It is estimated that the gravity dams are the first water barriers in the history of human lives. A gravity dam is a heavy structure, which is made of concrete or masonry materials across the river to increase the volume and height of water. In fact, gravity dams are among the most common types of concrete dams that have received special attention because of their simple design and their applications in different types of valleys. The stability of a concrete gravity dam entirely depends on its mass. Normally, the weight of a gravity dam suffices for stability against all design loads. Although gravity dams have been constructed in different shapes, they are generally made with roughly triangular cross-sections [1]. They had been built with masonry materials before the 1800s [2]. Nowadays, they are mostly constructed with concrete. Trapezoidal and rectangular profiles were used to build the first samples of gravity dams' cross-sections. Although the recent dams' shapes have emerged by the development of new materials and design techniques, which aim to find more optimal shapes by researches and civil engineers.

Optimization is an interesting technique in hydraulic structures design, which aims to find the best solution by searching the design variables in the search space [3]. Many studies in water engineering have been performed using various intelligent techniques, including spillways [3–7], reservoirs [8–10], earth dams [11], evaporation [12].

Generally, the structural optimization problems can be divided into three categories:(I) size optimization, (II) shape optimization, and (III) topology optimization [13]. Optimal design of dams can be done using mathematical methods or intelligent techniques like nature-inspired algorithms. The nature-inspired algorithms or in general metaheuristics tend to be better than the traditional methods on challenging, real-world problems due to the following reasons:

- As traditional algorithms are mostly local search and gradient-based, so there is no guarantee for finding the global optimum due to the existence of a large number of local solutions in real-world problems. Consequently, the final solution will often depend on the initial starting points.
- As traditional algorithms normally employ some information like derivatives about the local objective, they tend to be problem-specific.
- Traditional algorithms are not able to solve highly nonlinear, multimodal problems efficiently, and they struggle to cope with problems with discontinuity, especially when gradients are needed.

Different techniques have been employed to optimize gravity dams. Salmasi [14] optimized a gravity dam section using the genetic algorithm. Khatibinia and Khosravi [15] solved shape optimization problem of a concrete gravity dam using an improved gravitational search algorithm. Deepika and Suribabu [16] used Differential Evolution (DE) algorithm in order to find the best optimal shape of a gravity dam. The best solution was compared with an analytical model and the results showed about 20% reduction in concrete usage of dam. Kaveh and Zakian [13] optimized a concrete gravity dam section using Charged System Search (CSS), Colliding Bodies Optimization (CBO), and Enhanced Colliding Bodies Optimization (ECBO) algorithms. The results were compared to DEA results of Deepika and Suribabu [16]. All three used algorithms had superior results to DEA. Chiti et al. [17] optimized a gravity dam shape subjected to earthquake load based on reliability–based design optimization. Khatibinia et al. [18] used the hybrid of an improved gravitational search algorithm and the orthogonal crossover to optimum design of concrete gravity dams. Memarian and Shahbazi [19] used DE algorithm in optimization of some gravity dams' prototypes under various constraints. Zhang et al. [20] studied shape optimization of high RCC gravity dams regarding hydraulic fracturing. Apart from the aforementioned works, numerous problems in civil engineering have been solved using intelligent methods or, in general, soft computing methods [21–24].

Considering the No Free Lunch theorem [25] in optimization, which logically proves that there is no optimization algorithm to solve all optimization problems, designers need to evaluate various algorithms on a specific problem to see if it is better than others or not. Therefore, in the present study, a nature-inspired algorithm (i.e., invasive weed optimization algorithm) is employed to solve shape optimization problem of a concrete gravity dam based on two models geometry, considering a real benchmark design problem (i.e., Tilari Dam in Maharashtra, India). The selected gravity dam was optimized using some evolutionary algorithms in the previous works, which their results are compared to the current findings. Besides, in the present research, design variables bounds are changed to find better solutions for shape optimization problem of the concrete gravity dam.

2. Methodology

Nature-inspired approach, as a branch of artificial intelligence (AI), was chosen in the present study because intelligent methods are far faster and more precise than traditional methods and have viable results in the previous works. Optimization algorithms have different parameters, which should be determined at first step of optimization. These parameters are calculated using sensitivity analysis. The mathematical model of the problem is built considering the major factors and all design parameters. This model includes objective function of the problem (i.e., the area of gravity dam cross-section), design variables, and constraints. Penalty function technique is employed to consider them into objective function.

2.1. Invasive weed optimization

Invasive Weed Optimization (IWO) algorithm is one of the nature-inspired algorithms, which inspired by colonizing weeds and was introduced by Mehrabian and Lucas [26]. Comparison of the results of the IWO with four types of Evolutionary Algorithms (EAs) such as Genetic Algorithms (GAs), Memetic Algorithms (MAs), Particle Swarm Optimization (PSO) and Shuffled Frog Leaping Algorithms (SFLA) showed superior performance and convergence rate etc. [26]. Efficiency of IWO in optimization has been proved in different studies in water engineering [27–30].

The process of achieving the optimal solution in the IWO is as follows:

I. Initializing a population

The implementation of this algorithm begins with the distribution of a certain number of seeds (initial population) in the search space.

II. Reproduction

Each seed grows according to its merits and produces new seeds. The number of seeds produced by each plant increases linearly from the lowest possible number of seeds to the highest possible number.

III. Spatial dispersal

In this section, the generated seeds are randomly dispersed in the multidimensional search space by the normal random distribution. Its average value is zero and its standard deviation varies at different stages. This step is similar to the random propagation of the seeds around the parent plant. At each step, the value of the standard deviation σ corresponding to the random function is reduced from the initial value of $\sigma_{initial}$ to the final value of σ_{final}. In the simulations, the nonlinear change expressed in Eq. (1) has shown a performance:

$$\sigma_{iter} = \frac{(iter_{\max} - iter)^n}{(iter_{\max})^n}(\sigma_{initial} - \sigma_{final}) + \sigma_{final} \tag{1}$$

In Eq. (1), $iter_{max}$ represents the maximum number of iterations, σ_{iter} the standard deviation in the current time step, and n the nonlinear modulation index.

IV. Competitive exclusion

If the plant produces no seed, it will become extinct and otherwise, it can spread throughout the world. Therefore, some competition is needed to limit the maximum number of plants. After several iterations, the number of plants will reach their maximum. At this stage, it is expected that the more competent plants will proliferate than the other plants. When the number of plants reached its maximum (P_{max}), the process of removing plants begins with less fitness [26].

On the other hand, in the current study, IWO performance is compared to four algorithms in the literature i.e., Differential Evolution (DE), Charged System Search (CSS), Colliding Bodies Optimization (CBO), and Enhanced Colliding Bodies Optimization (ECBO). DE is one of the widely used metaheuristics, which can be categorized as a population based optimization algorithm. DE was developed by Storn and Price [31] and has been used in many real engineering complex problems by employing mutation, crossover, and selection operators' techniques. CSS is a population based algorithm, which was developed by Kaveh and Talatahari [32] and was inspired from Coulomb law from electrostatics and the Newtonian laws of classic mechanics. CBO algorithm is a metaheuristic, which was presented by Kaveh and Mahdavi [33]. Unlike the most of optimization algorithms, CBO works simply and does not depend on any internal parameter. ECBO is an improved version of CBO, which was proposed by Kaveh and Ilchi Ghazaan [34]. Colliding memory was employed in this algorithm in order to collect the best solutions. Techniques in harmony search algorithm were used to improve CBO.

2.2. Gravity dam optimum design model

Figure 1 shows the schematic of a gravity dam (plan and section). The purpose of shape optimizing of a structure is to find the most appropriate dimensions and shape so that it can withstand all loads and pressures. The loads in the gravity dam models are divided into two major categories including vertical and horizontal loads. The vertical loads include self-weight, uplift pressure force, silt pressure force, and seismic force. In addition, the vertical loads include water force, silt pressure force, wave pressure force, and seismic forces. Sliding and shear failure occur when the horizontal forces on each horizontal plane of a dam exceed its shear strength. Overturning of the dam and additional compressive stresses (and possibly tensile) can be prevented by selecting the appropriate cross-section. Normally, a gravity dam may be failed due to one or all of these reasons:

1) sliding on a horizontal plane
2) overturning on toe
3) weakness in material (stress > allowable stress)

Design constraints are normally related to safety consideration according to the nature of the engineering problems and design codes. The architectural and usability issues may be also considered as design constraints, but these issues are generally considered as the solution ranges of design variables to constrain the generation of possible optimum solutions. An optimization problem requires objective function(s) or cost function(s), which is widely related to the cost of the design, but safety, usability and architectural problems can be added into the formulation [35]. The design variables directly affect the objective function, which their values are unknown at the beginning of solving problems. Evolutionary algorithms based on the optimization process obtain their values. The calculated values of design variables must be within a desired range. The optimal solution is acceptable in case it contains all constraints and limitations in design problem. To apply constraints, penalty function is usually employed to consider them into an objective function [3,36,37].

The objective function in optimization of the gravity dam's shape is formulated as follows:

$$Minimize\ \ A_{dam} = 0.5x_1x_2 + BH + 0.5x_3x_4 \tag{2}$$

where A_{dam} is the area of gravity dam cross-section (m^2) and other parameters are shown in Fig. 1. The fitness function is formulated as Eq. (3) to include penalty functions (constraints) into the objective function (Eq. (2)).

$$Fitness\ \ Function = A_{dam} + \sum_{i=1}^{m} f_p \Psi \tag{3}$$

where f_p = penalty values; Ψ = a large integer number which makes the objective function unacceptable (in the case of penalty ≠ 0); and m = number of constraints.

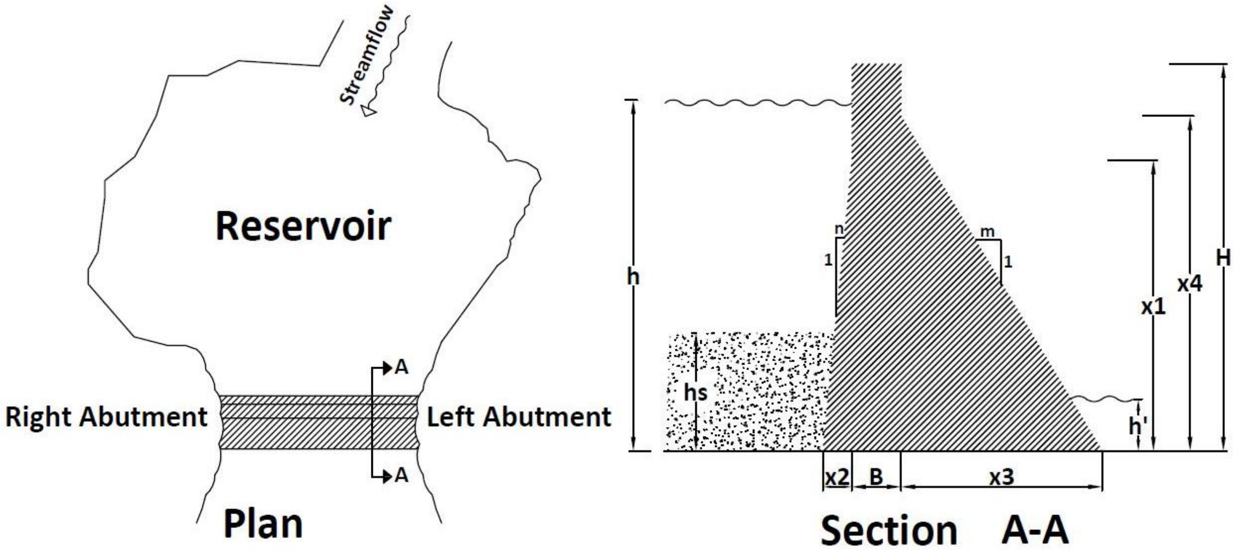

Fig. 1. A gravity dam schematic including geometric parameters.

Various loads affect gravity dams design. They can be categories into two major group: vertical and horizontal loads. The forces in the gravity dam design can be presented as follows:

A. Vertical forces

1) Self-weight: force × (liver arm about toe)

$$W_1 = \frac{1}{2}\gamma_c x_1 x_2 \times \left(x_3 + B + \frac{1}{3}x_2 \right) \tag{4}$$

$$W_2 = \gamma_c BH \times \left(x_3 + \frac{B}{2} \right) \tag{5}$$

$$W_3 = \frac{1}{2}\gamma_c x_3 x_4 \times \left(\frac{2}{3}x_3 \right) \tag{6}$$

$$P_{V_1} = \frac{1}{2}\gamma_w x_1 x_2 \times \left(x_3 + B + \frac{2}{3}x_2 \right) \tag{7}$$

$$P_{V2} = \gamma_w x_2 (h - x_1) \times \left(x_3 + B + \frac{1}{2}x_2 \right) \tag{8}$$

$$P_{V'} = \frac{1}{2}\gamma_w (mh')h' \times \left(\frac{mh'}{3} \right) \tag{9}$$

2) Uplift pressure force: force × (liver arm about toe)

$$U_1 = \frac{1}{3}\gamma_w (x_2 + d_g)(h - h^{'}) \times \left(x_3 + B + \frac{1}{3}(2x_2 - d_g) \right) \tag{10}$$

$$U_2 = \frac{1}{3}\gamma_w (x_2 + d_g)(h + 2h^{'}) \times \left(x_3 + B + \frac{1}{2}(x_2 - d_g) \right) \tag{11}$$

$$U_3 = \frac{1}{2}\gamma_w (x_3 + B - d_g)(\frac{h - h^{'}}{3}) \times \left(\frac{2}{3}(x_3 + B - d_g) \right) \tag{12}$$

$$U_4 = \gamma_w (x_3 + B - d_g)h^{'} \times \left(\frac{1}{2}(x_3 + B - d_g) \right) \tag{13}$$

3) Silt pressure force: force × (liver arm about toe)

$$P_{Vs} = \frac{1}{2} \times 0.925\gamma_w n h_s^2 \times \left(x_3 + B + x_2 - \frac{nh_s}{3} \right) \tag{14}$$

4) Seismic force: force × (liver arm about toe)

$$EV_1 = \alpha_v W_1 \times \left(x_3 + B + \frac{1}{3}x_2 \right) \tag{15}$$

$$EV_2 = \alpha_v W_2 \times \left(x_3 + \frac{B}{2} \right) \tag{16}$$

$$EV_3 = \alpha_v W_3 \times \left(\frac{2}{3}x_3 \right) \tag{17}$$

$$EV_4 = \alpha_v P_{V_1} \times \left(x_3 + B + \frac{2}{3}x_2 \right) \tag{18}$$

$$EV_5 = \alpha_v P_{V_2} \times \left(x_3 + B + \frac{1}{2}x_2 \right) \tag{19}$$

$$EV_6 = \alpha_v P_{V^{'}} \times \left(\frac{mh^{'}}{3} \right) \tag{20}$$

B. Horizontal forces

1) Water force: force × (liver arm about toe)

$$P_H = \frac{1}{2}\gamma_w h^2 \times \left(\frac{h}{3} \right) \tag{21}$$

$$P_{H^1} = \frac{1}{2}\gamma_w h^{'2} \times \left(\frac{h^{'}}{3} \right) \tag{22}$$

2) Silt pressure force: force × (liver arm about toe)

$$P_{H_s} = \frac{1}{2} \times 0.36 \gamma_w h_s^{\ 2} \times \left(\frac{h_s}{3} \right) \tag{23}$$

3) Wave pressure force: force × (liver arm about toe)

$$P_W = 2 \gamma_w h_w^{\ 2} \times \left(h + \frac{3}{8} h_w \right) \tag{24}$$

4) Seismic forces: force × (liver arm about toe)

$$EH_1 = \alpha_H W_1 \times \left(\frac{x_1}{3} \right) \tag{25}$$

$$EH_2 = \alpha_H W_2 \times \left(\frac{H}{2} \right) \tag{26}$$

$$EH_3 = \alpha_H W_3 \times \left(\frac{x_4}{3} \right) \tag{27}$$

$$\begin{aligned} P_{eH} &= 0.726 p_{eH} h \\ p_{eH} &= C_m \alpha_H \gamma_w h \\ M_{eH} &= 0.299 C_m \alpha_H \gamma_w h^3 \end{aligned} \tag{28}$$

$$\begin{aligned} P_{eH'} &= 0.726 p_{eH'} h' \\ p_{eH'} &= C'_m \alpha_H \gamma_w h' \\ M_{eH'} &= 0.299 C'_m \alpha_H \gamma_w h'^3 \end{aligned} \tag{29}$$

In optimization and design of structures, values of some parameters are fixed. In fact, they have been chosen by the experience or using previous experiments, design, and experiences, codes and by designer judgment. These fixed parameters in the gravity dam problem of Tilari Dam are as follows:

1. Dam height (H)= 38.55 m
2. Maximum (upstream) water level (h)= 36.2 (m)
3. Maximum (downstream) water level (h')= 3 (m)
4. Silt deposit level (h_s)= 13 (m)
5. Specific weight density of water (γ_w)= 9.81 (kN/m3)
6. Specific weight density of concrete (γ_c)= 2.4γ_w
7. Friction coefficient of (μ)= 0.75
8. Permissible shear stress at foundation (q)= 1200 (kPa)
9. Permissible compressive strength of concrete (σ_c)= 3000 (kPa)

10. Crest width (B)= 4.9 (m)
11. Downstream face height (X_4)= 33.35 (m)
12. Fetch (f)= 10 (km)
13. Wind velocity (V_w)= 80 (km/h)
14. Centre of drainage gallery from axis (d_g)= 1 (m)

Five variables are selected as design variables. These variables and their upper and lower bounds are represented in Eq. (30). Two models are considered in present paper. Normally, the upstream and downstream slopes (n and m) are considered between 0–0.2, and 0.6–0.8, respectively [2] . These parameters in model I (M1) were chosen as 0.1-0.2 and 0.6-0.9 according to studies of [13] and [16]. In model II (M2) the upper face of gravity dam is considered perpendicular (n=0).

$$Design\ \text{variables}\begin{cases} 0.1 \le n \le 0.2 \\ 0.6 \le m \le 0.9 \\ 0.8h \le x_1 \le 0.95h \\ 0.05 \le a_v \le 0.2 \\ 0.05 \le a_h \le 0.2 \end{cases} \tag{30}$$

Stability (overturning and sliding), stress, and geometry constraints are applied in shape optimization in the current study. The stability and stress constraints are shown in Eqs. (31) and (32). The geometry constraints are applied to the problem using upper and lower bounds on design variables.

$$Constraints\begin{cases} \text{Stability}\begin{cases} Overturning \rightarrow FOS = \dfrac{\sum M_R}{\sum M_O} \ge 1.5 \\ Sliding \rightarrow FSS = \dfrac{\mu \sum F_V}{\sum F_H} \ge 1 \\ Shear\ Friction\ Factor \rightarrow SFF = \dfrac{\mu \sum F_V + qB_1}{\sum F_H} \ge 3 \end{cases} \\ Stress\begin{cases} Principal\begin{cases} Toe \rightarrow \sigma_{pD} \le \sigma_c \\ Heel \rightarrow \sigma_{pU} \le \sigma_c \end{cases} \\ Shear\begin{cases} Toe \rightarrow \tau_{xyD} \le \sigma_c \\ Heel \rightarrow \tau_{xyU} \le \sigma_c \end{cases} \end{cases} \end{cases} \tag{31}$$

in which

$$\begin{aligned} \sigma_{pD} &= \sigma_{yD} \sec^2 \phi_D - (p'_H - p_{eH'}) \tan^2 \phi_D \\ \sigma_{pU} &= \sigma_{yU} \sec^2 \phi_U - (p_H - p_{eH}) \tan^2 \phi_U \\ \tau_{xyD} &= [\sigma_{yD} - (p'_H - p_{eH'})] \tan \phi_D \\ \tau_{pU} &= [\sigma_{yU} - (p_H + p_{eH})] \tan \phi_U \end{aligned} \tag{32}$$

where $\sigma_{yD} = \frac{\sum F_V}{B_1}(1+\frac{6e}{B_1})$, $p'_H = \gamma_w h'$, $\sigma_{yU} = \frac{\sum F_V}{B_1}(1+\frac{6e}{B_1})$, and $p_H = \gamma_w h$.

3. Results and discussions

Sensitivity analysis for choosing the IWO parameters was conducted and its results are shown in Table 1. In fact, sensitivity analysis is necessary to gain the best value of the objective function. Considering Table 1, eight parameters should be evaluated prior to employing the IWO in real engineering problems. Some algorithms have more parameters to tune than others such as the IWO. Different values were examined to determine initial population, maximum number of plants population, minimum number of seeds, maximum number of seeds, nonlinear modulation index, initial value of standard deviation, final value of standard deviation, and maximum number of iterations, but the most appropriate ones in solving the concrete gravity dam problem are shown in Table 1.

In Fig. 2, the convergence of the objective function for M1 using the IWO is shown. As it is obvious, the objective function of shape optimization problem converged in 50 iterations.

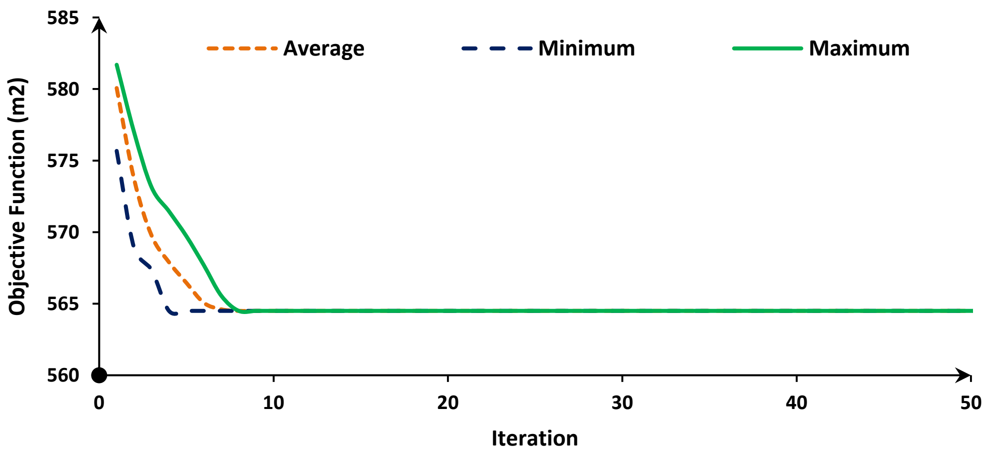

Fig. 2. Convergence for IWO.

Optimization results of two studied models and algorithms in previous works i.e., Differential Evolution (DE), Charged System Search (CSS), Colliding Bodies Optimization (CBO), and Enhanced Colliding Bodies Optimization (ECBO) are shown in Table 2. In addition, Tilari Dam parameters are shown in aforementioned table. The cross-sectional area of this dam, which was constructed in India, is 709.493 (m2). As dams are normally constructed in wide valleys, small changes in their cross-sectional area lead to high-cost saving. M1 has the same upper and lower bounds as studies of [13] and [16]. According to the results, IWO with same conditions of DE, CSS, CBO, and ECBO could find the same objective function of them. In other words, IWO (M1), DE, CSS, CBO, and ECBO were succeeded in reducing total cross sectional area on Tilari Dam more than 20% i.e., decrease from 709.493 (m2) to 564.496. The upstream and downstream slope faces and parameter *x1* in these optimal models were 0.1, 0.6, and 28.96, respectively.

Table 1
Parameters of IWO.

Parameter	**Symbol**	**Value**
Number of initial population	N_0	10
Maximum number of plant population	p_{max}	100
Minimum number of seeds	S_{min}	2
Maximum number of seeds	S_{max}	5
Nonlinear modulation index	n	3
Initial value of standard deviation	$\sigma_{initial}$	1
Final value of standard deviation	σ_{final}	0.001
Maximum number of iterations	it_{max}	50

In M2, gravity dam model had vertical upstream face. This situation can reduce dam's mass and water weight in upstream (resisting moments), and cross-sectional area. The results showed the gravity dam with perpendicular upstream face could lead to a far more economical design. Total cross-sectional area in M2 was calculated 522.56 (m2), which had about 26% reduction in comparison with prototype model (Tilari Dam). In M2 the calculated values of the parameters a_v and ah were more than other optimal models. It is worth mentioning that these two parameters are chosen based on seismicity of dam's zone. This issue was mentioned in [13], too. In fact, the more seismicity in dam's site causes the more increase in the value of *ah*. In some studies is proposed to choose parameter a_v value of 1/2 or 2/3 of a_h. Generally, the magnitude of an earthquake depends on various parameters such as dam's weight and type, dam's material behavior, and earthquake magnitude. Stability, stress, and geometry constraints (Eq. (31)) were applied in the current problem to ensure real-dam-design conditions. These constraints were between desired limits, which are shown in Eqs. (30) and (31).

Table 2
Parameters of prototype and optimal models.

Design variable	Tilari Dam	Algorithm					
		IWO (M1)	IWO (M2)	DE [16]	CSS [13]	CBO [13]	ECBO [13]
n	0.1	0.1	0	0.1	0.1	0.1	0.1
m	0.85	0.6	0.6	0.6	0.6	0.6	0.6
$x1$ (m)	30.95	28.96	-	28.96	28.96	28.96	28.96
a_v	-	0.05	0.2	0.053	0.0589	0.0502	0.05
a_h	-	0.05	0.1491	0.064	0.0558	0.0514	0.05
Cross-sectional area (m^2)	709.493	564.49583	522.56175	564.496	564.49583	564.49583	564.49583

6. Conclusions

Without any doubt, optimization techniques could reduce the construction time and costs. Among all infrastructures, gravity dams consume the sheer volume of materials. Accordingly, small changes in their geometries cause a major variation in the construction time and costs. In the current study, a nature-inspired algorithm, namely invasive weed optimization (IWO) was employed to optimize the shape of a concrete gravity dam. A real benchmark design problem (i.e., Tilari Dam, which is built in the India, with 709.493 m2 cross-sectional area) is used as a case study. The current framework can also be used in the future designs of other gravity dams. The performance of IWO was also compared to four algorithms in the literature: differential evolution (DE), charged system search (CSS), colliding bodies optimization (CBO), and enhanced colliding bodies optimization (ECBO). Various vertical and horizontal loads (i.e., water, seismic, wave, uplift, silt and so on) affect design of dams so the programming model should contain all of them. Two models were presented and their results were compared to four aforementioned algorithms. First model (M1) had the same conditions as the previous works. While the IWO had the same result compared to DE, CSS, CBO, and ECBO, convergence graph showed that the IWO converges faster than them. M1 and those four models in the literature reduced cross-sectional area of Tilari Dam approximately 20 percent. It is worth mentioning that in the gravity dams design, like any real design problem, there are different methods and codes and their consequent certain coefficients and considerations, which must be considered as well in order to compare the results obtained by different works. In addition, model 2 (M2) was proposed to evaluate a different condition i.e., a concrete gravity dam with perpendicular upstream face. According to the results, the cross-sectional area which was optimized with this assumption needed 26 percent less amount of concrete than real design. In summary, IWO could design a cross section for the gravity dam with a better vertical upstream face which endures all vertical and horizontal loads and had less concrete volume.

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Conflicts of interest

The authors declare no conflict of interest.

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